

Vorlesung Graphenzeichnen: Order in the Underground *or* How to Automate the Drawing of Metro Maps

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Lehrstuhl für Algorithmik I

26.06.2008

Outline

- Modeling the Metro Map Problem
 - What is a Metro Map?
 - Hard and Soft Constraints
- NP-Hardness: Bad News—Nice Proof
 - Rectilinear vs. Octilinear Drawing
 - Reduction from PLANAR 3-SAT
- MIP Formulation & Experiments
 - Mixed-Integer Programming Formulation
 - Experiments
 - Labeling

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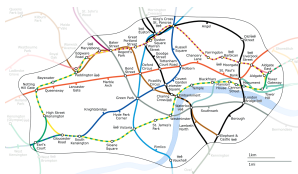
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What is a Metro Map?

- schematic diagram for public transport



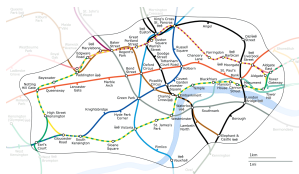
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- schematic diagram for public transport
- visualizes lines and stations



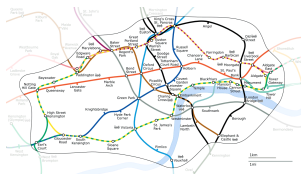
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- visualizes lines and stations
- goal: ease navigation for passengers
 - “How do I get from A to B?”
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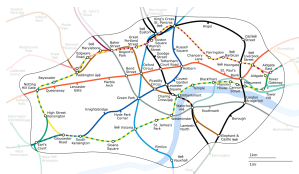


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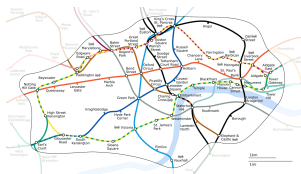
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- improves readability
- compromise between schematic road map ↔ abstract graph

Why Automate Drawing Metro Maps?

- current maps designed manually



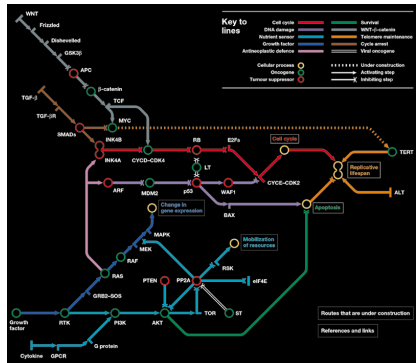
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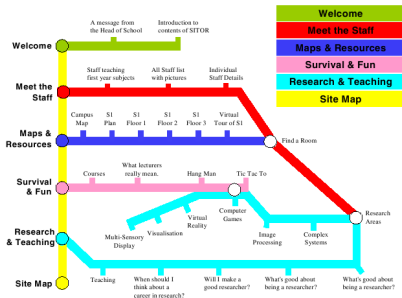
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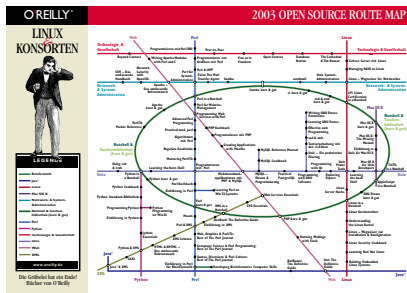
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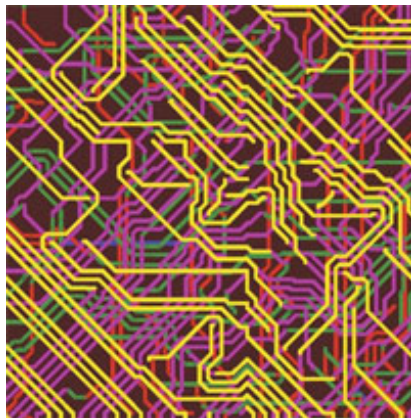
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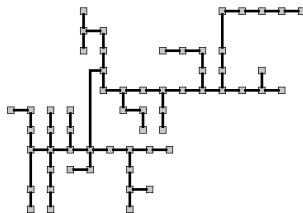
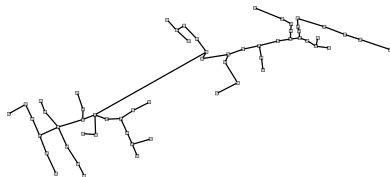
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- current maps designed manually
- assist graphic designers to improve/extend maps
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 - web page maps
 - product lines
- VLSI: X-architecture
- drawing sketches
[Brandes et al. '03]



More Formally

The Metro Map Problem

Given: planar embedded graph $G = (V, E)$, $V \subset \mathbb{R}^2$,
line cover \mathcal{L} of paths or cycles in G (the metro lines),
Goal: draw G and \mathcal{L} **nicely**.

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- What is a **nice** drawing?
- Look at real-world metro maps drawn by graphic designers and model their design principles as
 - *hard* constraints – must be fulfilled,
 - *soft* constraints – should hold as tightly as possible.

Hard Constraints

- (H1) preserve embedding of G
- (H2) draw all edges as **octilinear** line segments, i.e. horizontal, vertical or diagonal (45 degrees)



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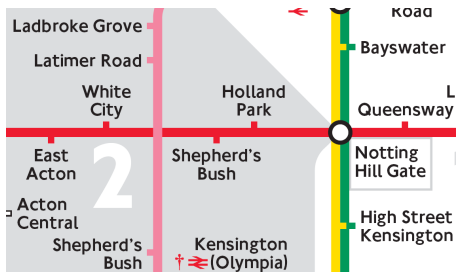
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- (H2) draw all edges as **octilinear** line segments, i.e. horizontal, vertical or diagonal (45 degrees)
- (H3) draw each edge e with length $\geq \ell_e$
- (H4) keep edges d_{\min} away from non-incident edges



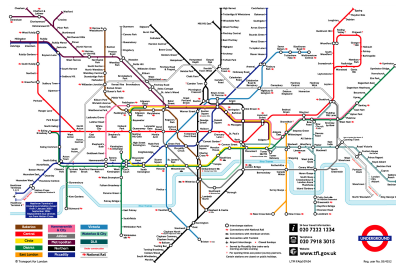
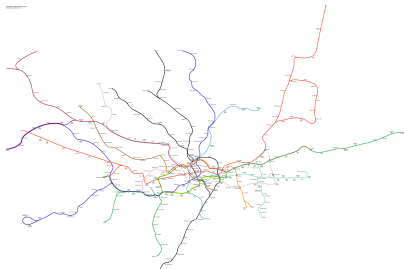
Soft Constraints

(S1) draw metro lines with few bends



Soft Constraints

- (S1) draw metro lines with few bends
- (S2) keep total edge length small



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Another Problem

RECTILINEARGRAPHDRAWING Decision Problem

Given a planar embedded graph G with max degree 4.
Is there a drawing of G that

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Our Problem

METROMAPLAYOUT Decision Problem

Given a planar embedded graph G with max degree **8**.

Is there a drawing of G that

- preserves the embedding,
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- is **octilinear**?

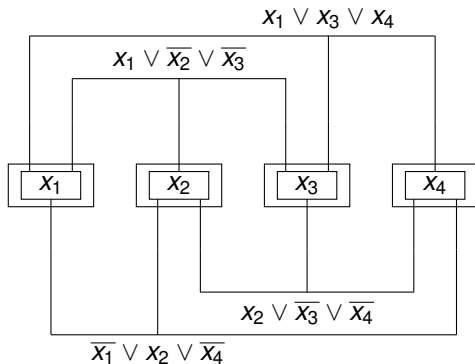
Theorem (Nöllenburg MSc'05)

METROMAPLAYOUT is **NP-hard**.

Proof.

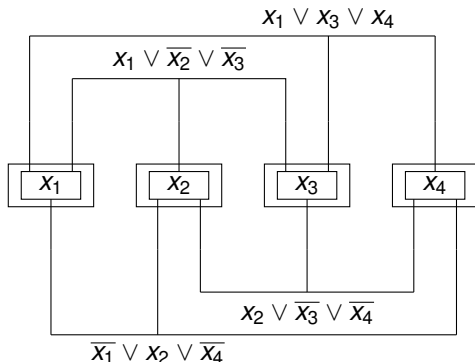
By Reduction from PLANAR 3-SAT to METROMAPLAYOUT. □

Outline of the Reduction



Input: planar 3-SAT formula $\varphi =$
 $(x_1 \vee x_3 \vee x_4) \wedge (x_1 \vee \overline{x_2} \vee \overline{x_3}) \wedge \dots$

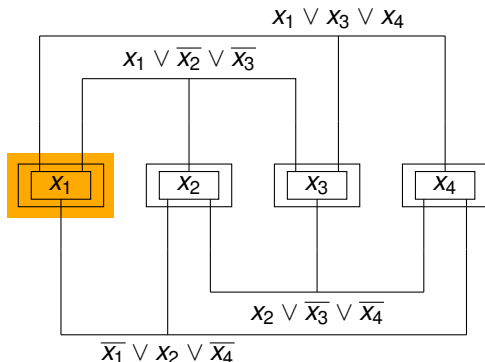
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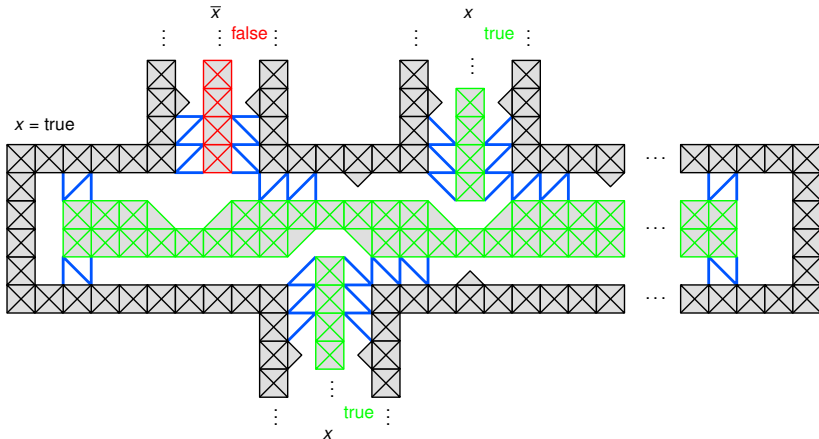
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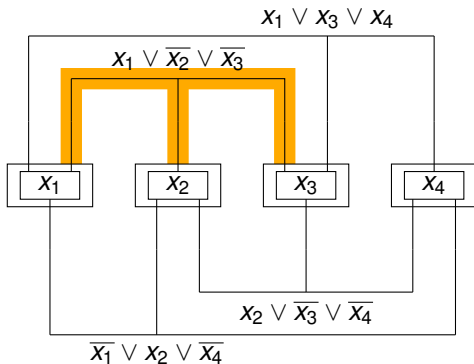
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Variable Gadget



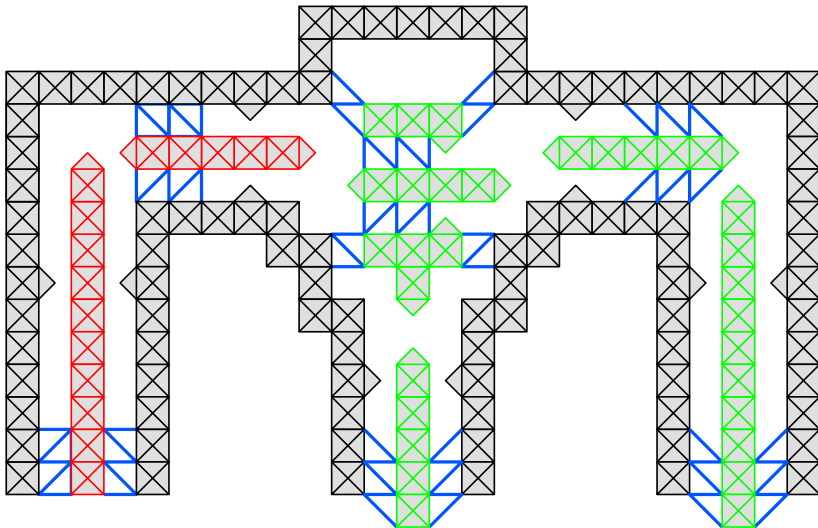
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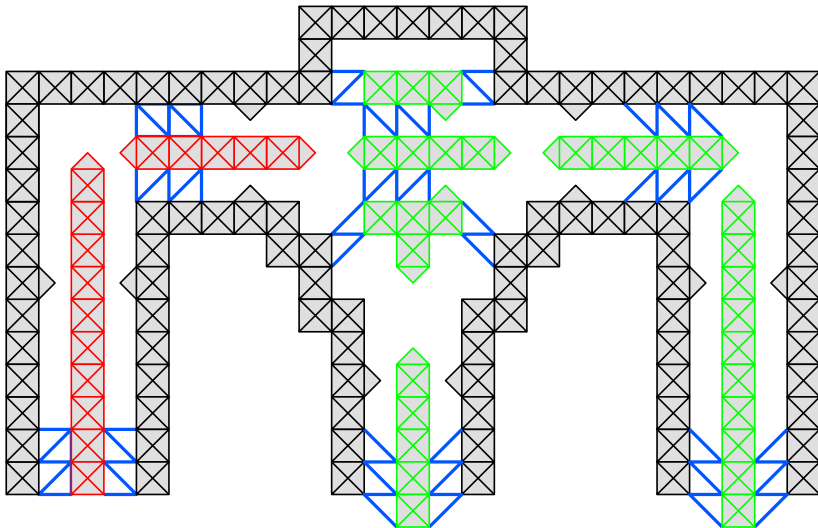
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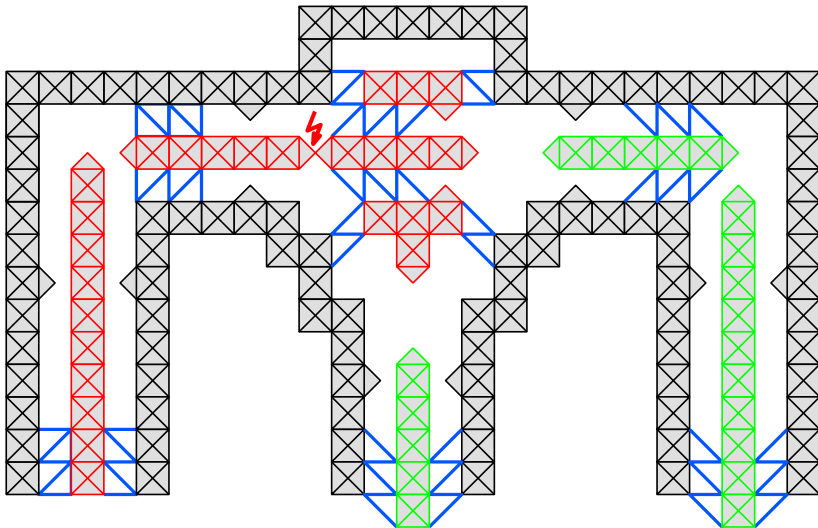
Clause Gadget



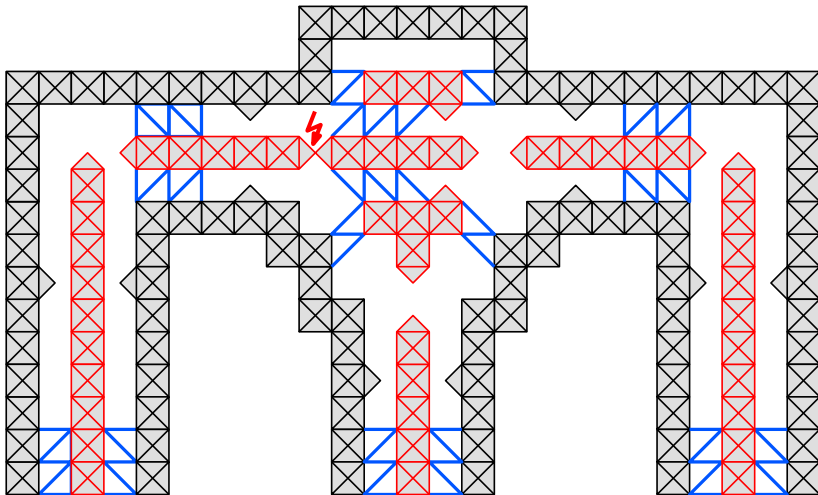
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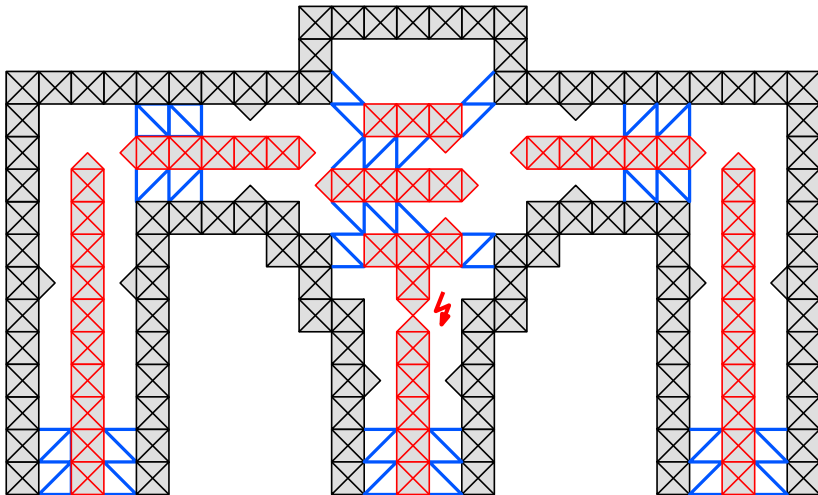
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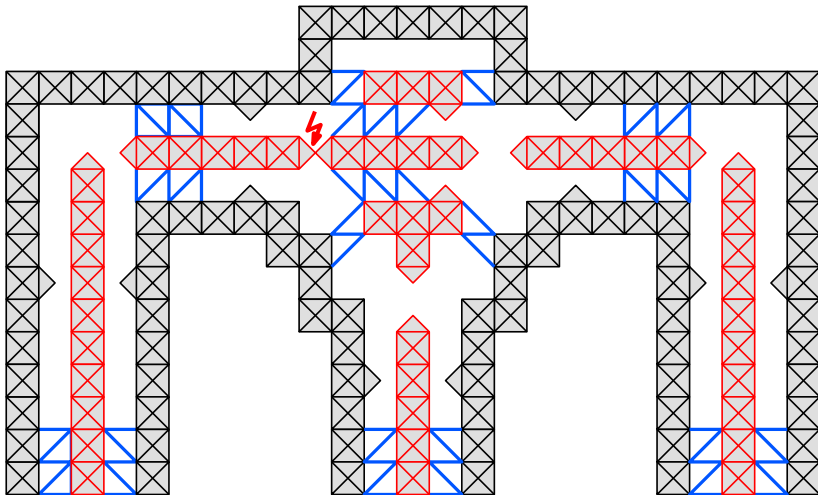
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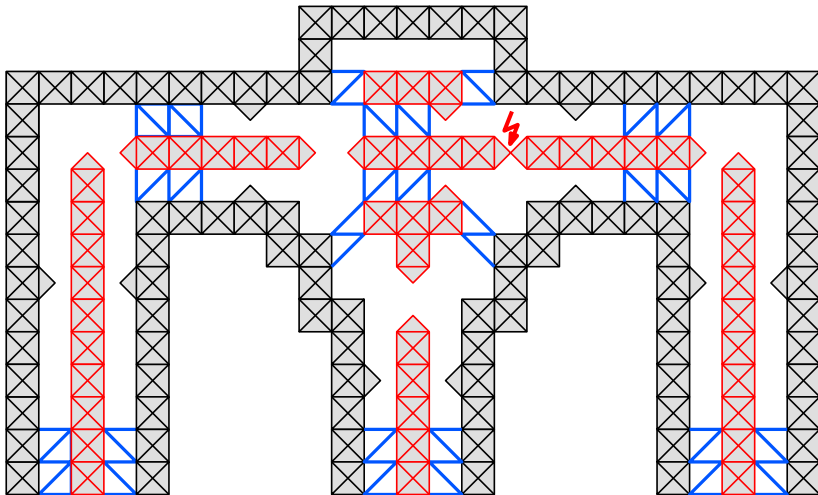
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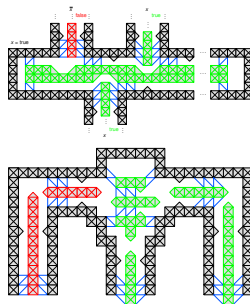
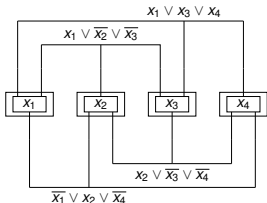
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Summary of the Reduction



• Indeed we have:

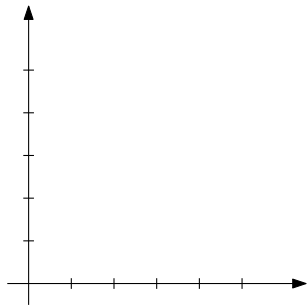
- φ satisfiable \Rightarrow corresponding MM drawing of G_φ
- G_φ has MM drawing \Rightarrow satisfying truth assignment of φ

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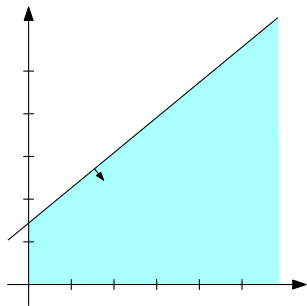
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- **Linear Programming**: efficient optimization method for
 - linear constraints
 - linear objective function
 - real-valued variables



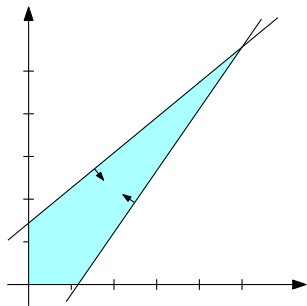
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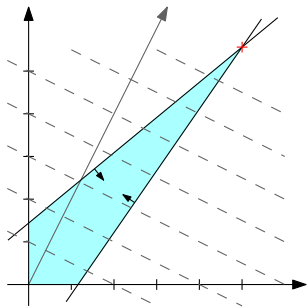
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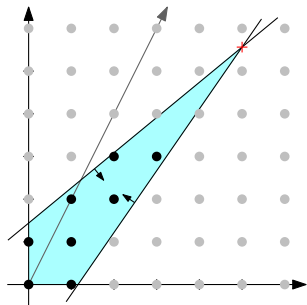
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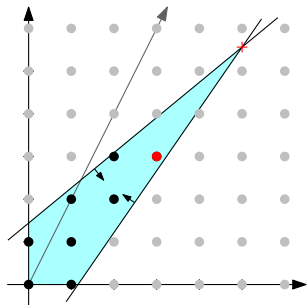
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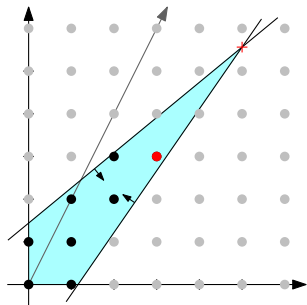
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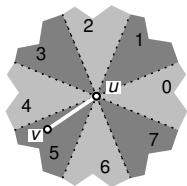
Theorem (Nöllenburg & Wolff GD'05)

The problem MetroMapLayout can be formulated as a MIP s.th.

hard constraints → *linear constraints*

soft constraints → *objective function*

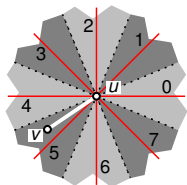
Definitions: Sectors and Coordinates



Sectors

- for each vtx. u partition plane into sectors 0–7
 - here: $\text{sec}(u, v) = 5$ (input)

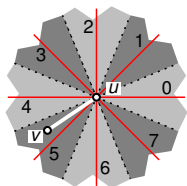
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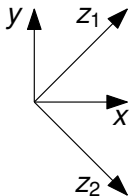
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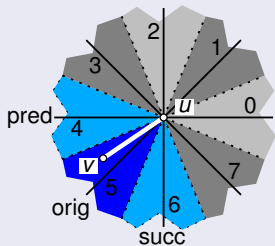
Coordinates

assign z_1 - and z_2 -coordinates to each vertex v :

- $z_1(v) = x(v) + y(v)$
- $z_2(v) = x(v) - y(v)$

Octilinearity and Relative Position

Goal

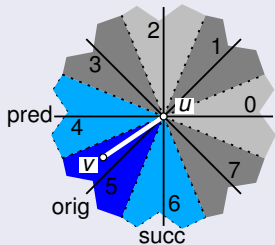


Draw edge uv

- octilinearly
- with minimum length ℓ_{uv}
- restricted to 3 directions

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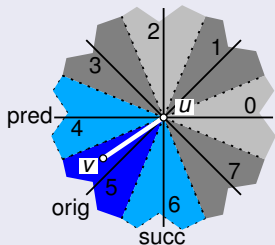
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How to model this using linear constraints?

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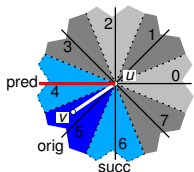
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How to model this using linear constraints?

Binary Variables

$$\alpha_{\text{pred}}(u, v) + \alpha_{\text{orig}}(u, v) + \alpha_{\text{succ}}(u, v) = 1$$

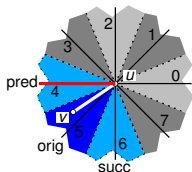
Octilinearity and Relative Position



Predecessor Sector

$$\begin{aligned}
 y(u) - y(v) &\leq M(1 - \alpha_{\text{pred}}(u, v)) \\
 -y(u) + y(v) &\leq M(1 - \alpha_{\text{pred}}(u, v)) \\
 x(u) - x(v) &\geq -M(1 - \alpha_{\text{pred}}(u, v)) + \ell_{uv}
 \end{aligned}$$

Octilinearity and Relative Position

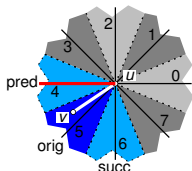


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How does this work?

Octilinearity and Relative Position



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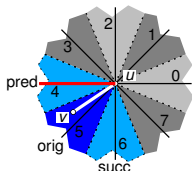
$$\begin{aligned} y(u) - y(v) &\leq M(1 - \alpha_{\text{pred}}(u, v)) \\ -y(u) + y(v) &\leq M(1 - \alpha_{\text{pred}}(u, v)) \\ x(u) - x(v) &\geq -M(1 - \alpha_{\text{pred}}(u, v)) + \ell_{uv} \end{aligned}$$

How does this work?

Case 1: $\alpha_{\text{pred}}(u, v) = 0$

$$\begin{aligned} y(u) - y(v) &\leq M \\ -y(u) + y(v) &\leq M \\ x(u) - x(v) &\geq \ell_{uv} - M \end{aligned}$$

Octilinearity and Relative Position



Predecessor Sector

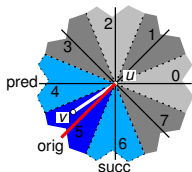
$$\begin{aligned}
 y(u) - y(v) &\leq M(1 - \alpha_{\text{pred}}(u, v)) \\
 -y(u) + y(v) &\leq M(1 - \alpha_{\text{pred}}(u, v)) \\
 x(u) - x(v) &\geq -M(1 - \alpha_{\text{pred}}(u, v)) + l_{uv}
 \end{aligned}$$

How does this work?

Case 2: $\alpha_{\text{prev}}(u, v) = 1$

$$\begin{aligned}
 y(u) - y(v) &\leq 0 \\
 -y(u) + y(v) &\leq 0 \\
 x(u) - x(v) &\geq l_{uv}
 \end{aligned}$$

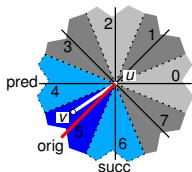
Octilinearity and Relative Position



Original Sector

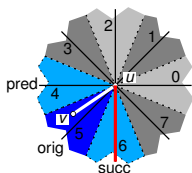
$$\begin{aligned}
 z_2(u) - z_2(v) &\leq M(1 - \alpha_{\text{orig}}(u, v)) \\
 -z_2(u) + z_2(v) &\leq M(1 - \alpha_{\text{orig}}(u, v)) \\
 z_1(u) - z_1(v) &\geq -M(1 - \alpha_{\text{orig}}(u, v)) + 2\ell_{uv}
 \end{aligned}$$

Octilinearity and Relative Position



Original Sector

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Successor Sector

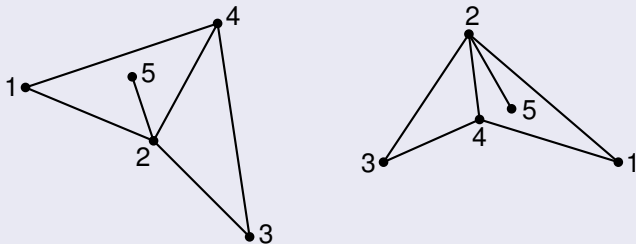
$$\begin{aligned} x(u) - x(v) &\leq M(1 - \alpha_{\text{succ}}(u, v)) \\ -x(u) + x(v) &\leq M(1 - \alpha_{\text{succ}}(u, v)) \\ y(u) - y(v) &\geq -M(1 - \alpha_{\text{succ}}(u, v)) + \ell_{uv} \end{aligned}$$

Preserving the Embedding

Definition

Two planar drawings of G have the same *embedding* if the induced orderings on the neighbors of each vertex are equal.

Same Embedding

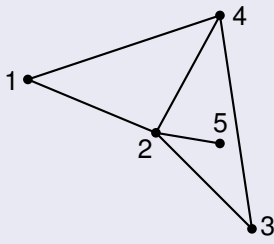
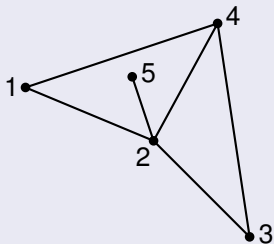


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Different Embeddings



Preserving the Embedding

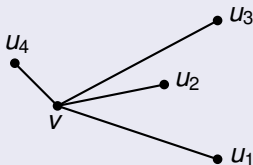
Constraints (Example)

- $N(v) = \{u_1, u_2, u_3, u_4\}$
- circular input order: $u_1 < u_2 < u_3 < u_4 < u_1$

All but one of the following inequalities must hold

$$\text{dir}(v, u_1) < \text{dir}(v, u_2) < \text{dir}(v, u_3) < \text{dir}(v, u_4) < \text{dir}(v, u_1)$$

Input



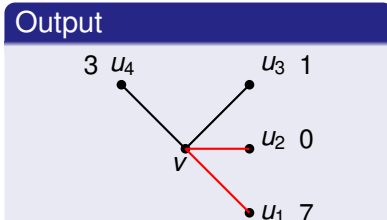
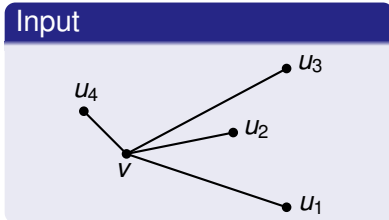
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$$\text{dir}(v, u_1) \not< \text{dir}(v, u_2) < \text{dir}(v, u_3) < \text{dir}(v, u_4) < \text{dir}(v, u_1)$$

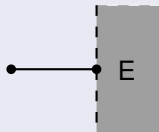


Planarity

Observation

For octilinear, straight edge e_1
non-intersecting edge e_2 must be placed

- **east**, northeast, north, northwest,
west, southwest, south, or southeast

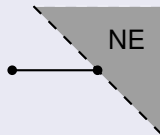


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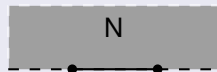


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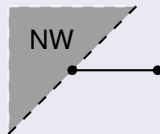


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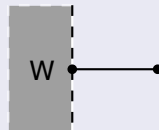


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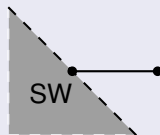


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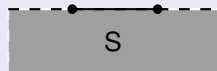


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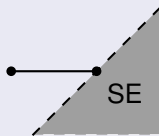


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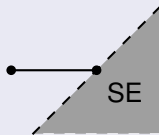


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Constraints

- model as MIP with binary variables
- need planarity constraints for each pair of non-incident edges

Objective Function

Objective Function

- corresponds to soft constraints (S1)–(S3)
- weighted sum of individual cost functions

minimize $\lambda_{\text{bends}} \text{cost}_{\text{bends}} + \lambda_{\text{length}} \text{cost}_{\text{length}} + \lambda_{\text{relpos}} \text{cost}_{\text{relpos}}$

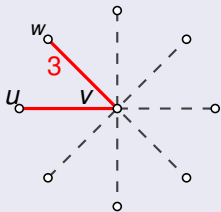
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Line Bends (S1)



Edges uv and vw on a line $L \in \mathcal{L}$

- draw as straight as possible
- increasing cost $\text{bend}(u, v, w)$ for increasing acuteness of $\angle(\overline{uv}, \overline{vw})$

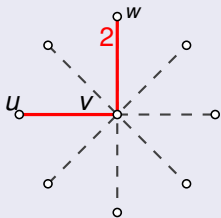
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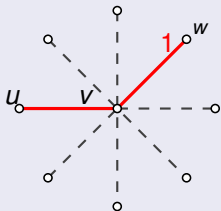
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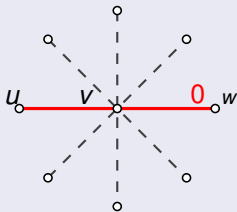
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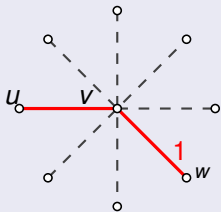
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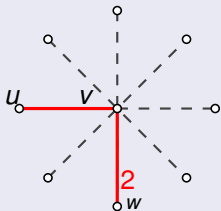
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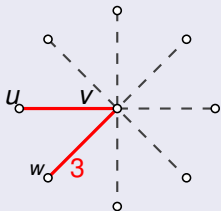
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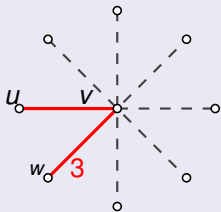
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Objective Function

Total Edge Length (S2)

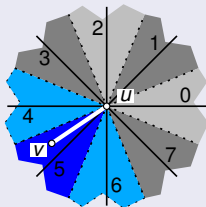
$$\text{cost}_{\text{length}} = \sum_{uv \in E} \text{length}(\overline{uv})$$

Objective Function

Total Edge Length (S2)

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Relative Position (S3)



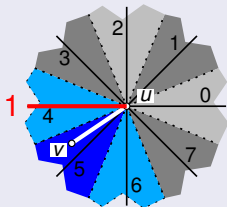
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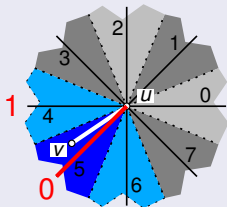
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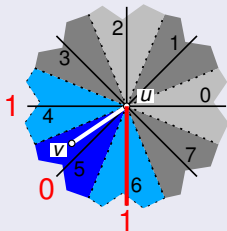
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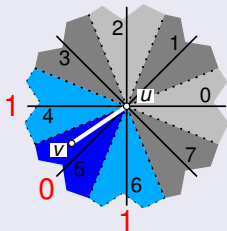
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Summary of the MIP

- hard constraints:
 - octilinearity
 - minimum edge length
 - (partially) relative position
 - preservation of embedding
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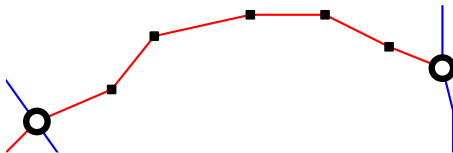
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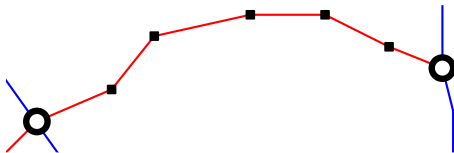
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Speed-Up Techniques: Reduce Graph Size



- metro graphs have many degree-2 vertices
- want to optimize line straightness

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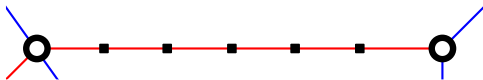
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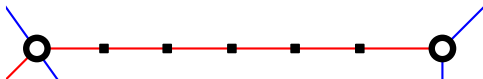
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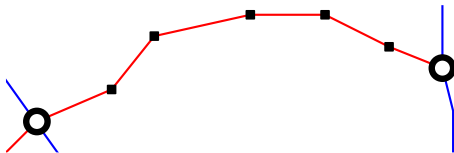


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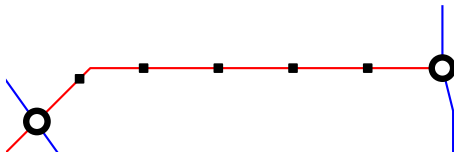
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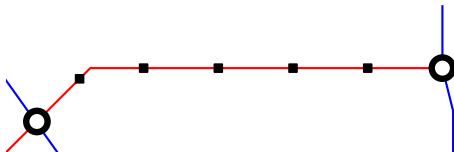
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Idea 2 keep two *joints*

- higher flexibility
- more similar to input

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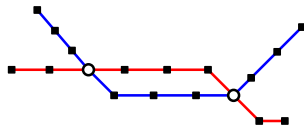
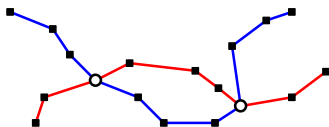
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- in practice no or only few crossings due to soft constraints



Speed-Up Techniques: Reduce MIP Size

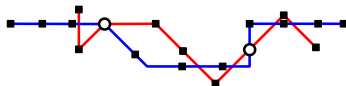
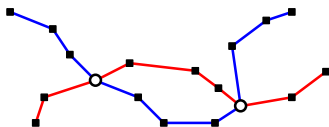
- $O(|V|^2)$ planarity constraints (for each pair of edges...)
- in practice 95–99% of constraints

Observation 1

- consider only pairs of edges incident to the same face
- still $O(|V|^2)$ constraints

Observation 2

- in practice no or only few crossings due to soft constraints



Speed-Up Techniques: Callback Functions

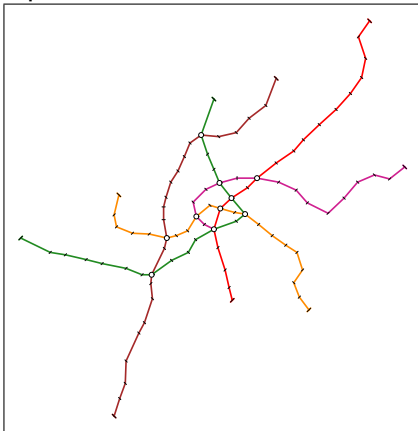
- MIP optimizer CPLEX offers advanced callback functions
- add required planarity constraints on the fly

Algorithm

- 1 start solving MIP without planarity constraints
- 2 for each new solution s
 - 1 interrupt CPLEX
 - 2 if s is not planar
 - add planarity constraints for edges that intersect in s
 - reject s
 - else
 - accept s
- 3 continue solving the MIP (until optimal)

Results – Vienna

Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	90	96	8	5
reduced	44	50	8	5

Results – Vienna

Input



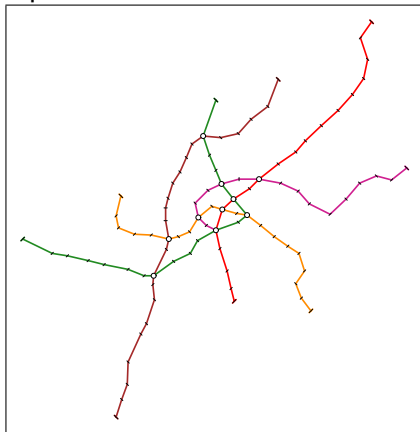
Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	90	96	8	5
reduced	44	50	8	5

↓

MIP	constr.	var.
normal	39,363	9,960
faces	23,226	6,048
callback	1,875	872

Results – Vienna

Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	90	96	8	5
reduced	44	50	8	5

↓

MIP	constr.	var.
normal	39,363	9,960
faces	23,226	6,048
callback*	1,875	872

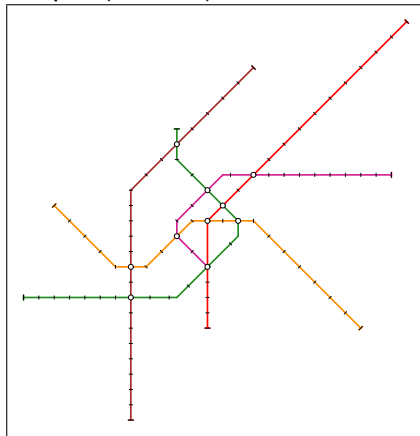
*) 21 seconds w/o proof of opt.

Results – Vienna

Input



Output (21 sec.)

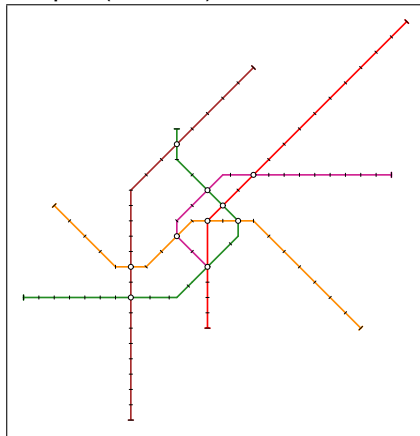


Results – Vienna

Official maps

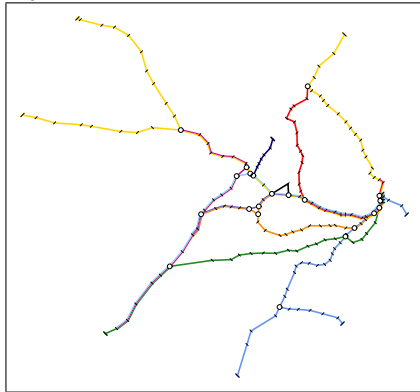


Output (21 sec.)



Results – Sydney

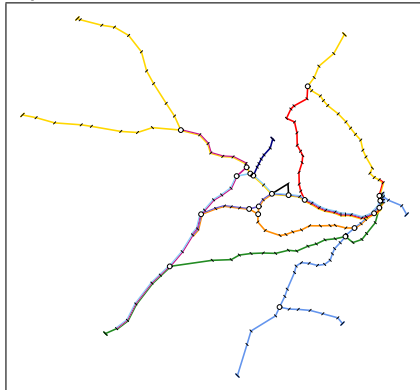
Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	174	183	11	10
reduced	67	76		

Results – Sydney

Input



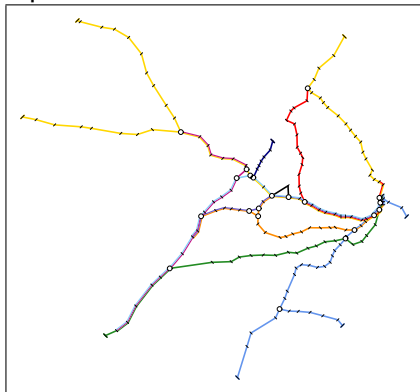
Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	174	183	11	10
reduced	67	76		



MIP	constr.	var.
normal	93,620	23,389
faces	52,568	13,437
callback	4,147	6,741

Results – Sydney

Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	174	183	11	10
reduced	67	76		

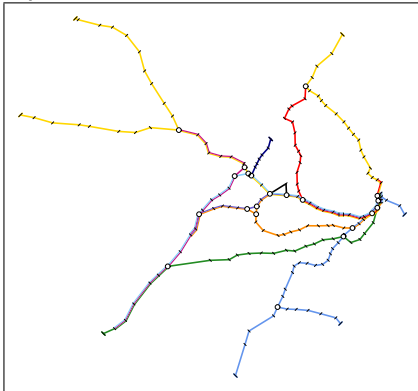
↓

MIP	constr.	var.
normal	93,620	23,389
faces	52,568	13,437
callback*	4,147	6,741

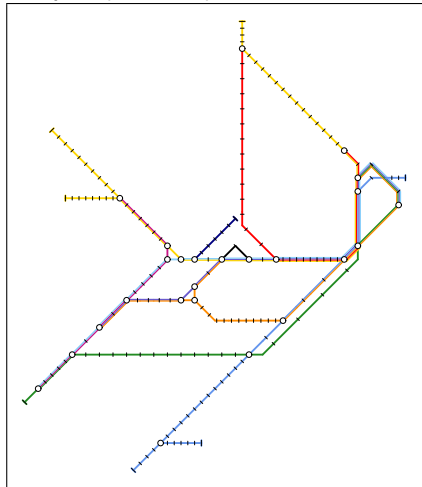
*) 33 seconds w/o proof of opt.
constr. of 4 edge pairs added

Results – Sydney

Input

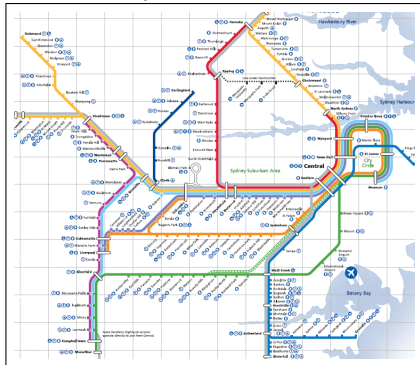


Output (33 sec.)

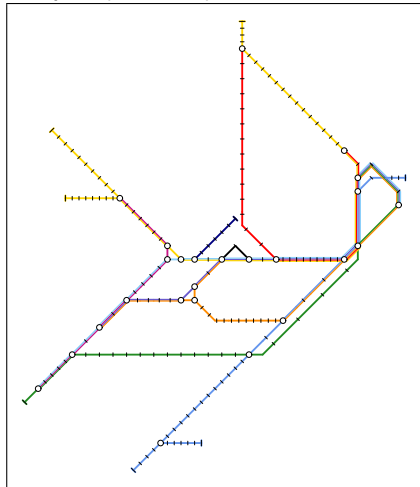


Results – Sydney

Official map

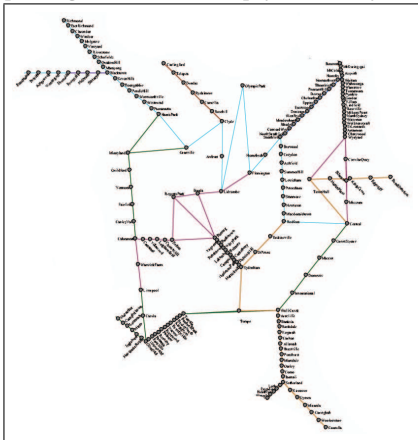


Output (33 sec.)

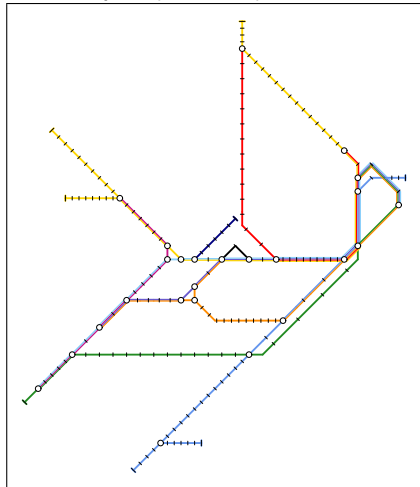


Sydney: Related Work

[Hong et al. GD'04] (7.6 sec.)

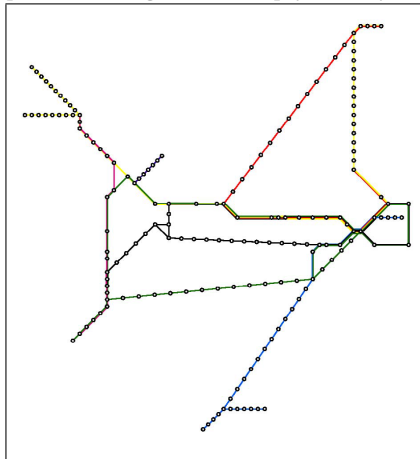


Our output (33 sec.)

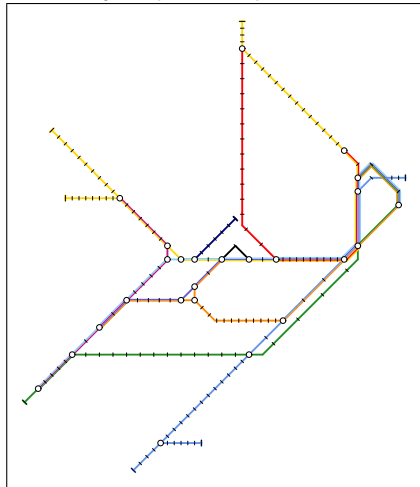


Sydney: Related Work

[Stott, Rodgers IV'04] (4 min.)

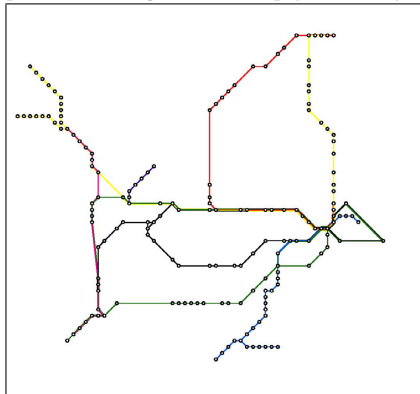


Our output (33 sec.)

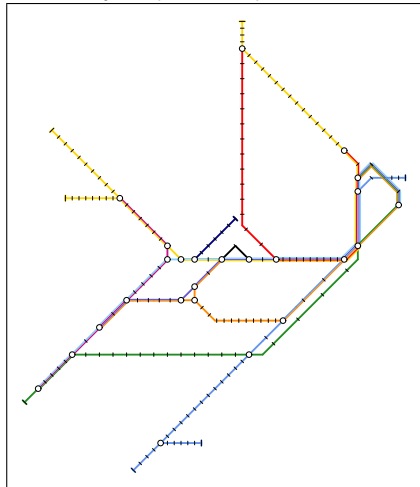


Sydney: Related Work

[Stott, Rodgers IV'04] (28 min.)

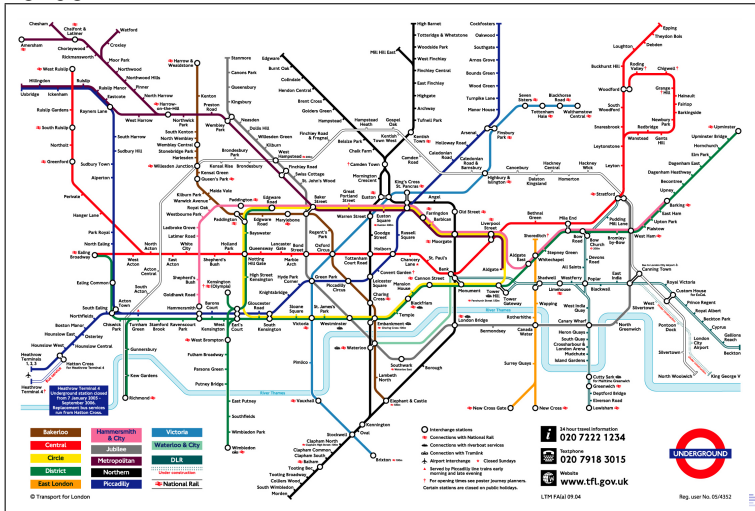


Our output (33 sec.)



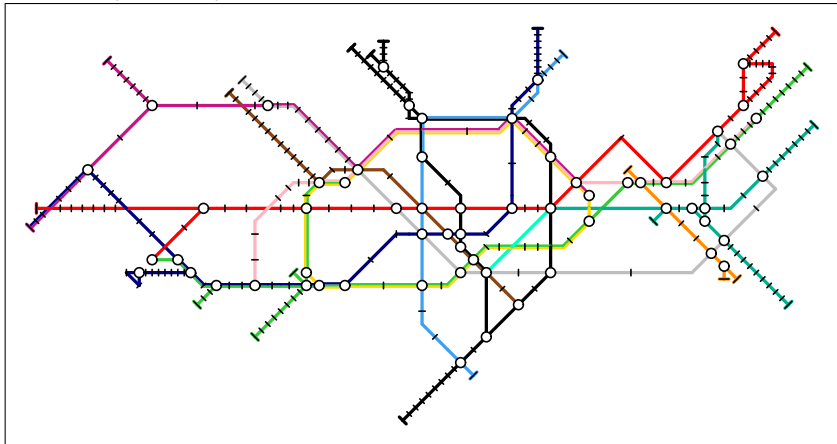
Large Maps

London



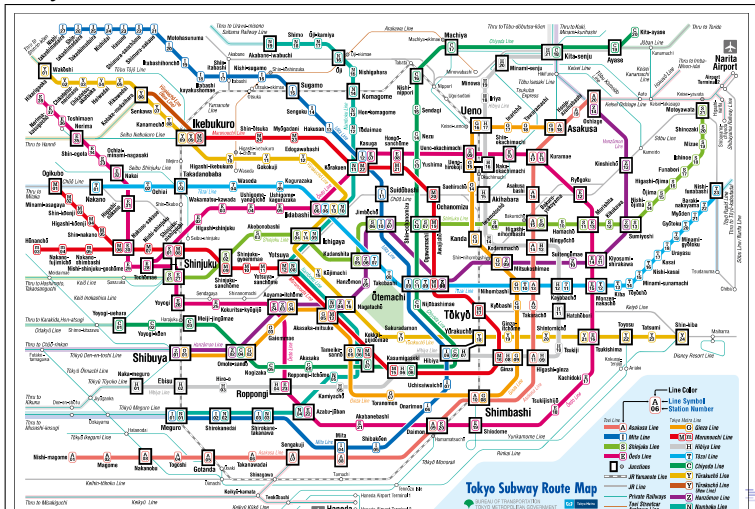
Large Maps

London (16 min.)



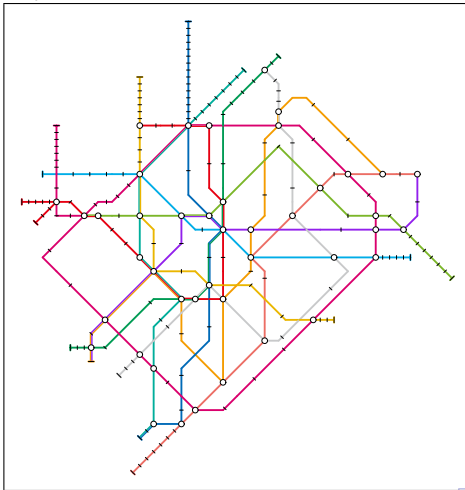
Large Maps

Tokyo



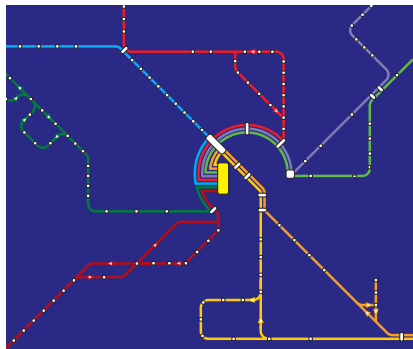
Large Maps

Tokyo (4:50 hrs.)



Labeling

- unlabeled metro map of little use in practice



Labeling

- unlabeled metro map of little use in practice
- labels
 - occupy space
 - may not overlap



Labeling

- unlabeled metro map of little use in practice
- labels
 - occupy space
 - may not overlap
- static map labeling is NP-hard

[Tollis, Kakoulis '01]



Labeling

- unlabeled metro map of little use in practice
- labels
 - occupy space
 - may not overlap
- static map labeling is NP-hard

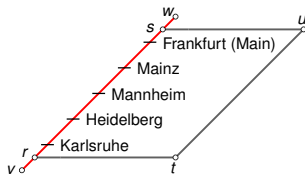
[Tollis, Kakoulis '01]
- want to combine layout and labeling for better results



Modeling Labels

Model labels as special metro lines:

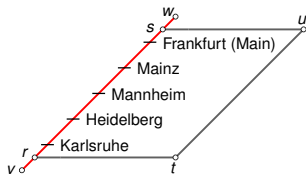
- put all labels between a pair of interchange stations into one parallelogram,



Modeling Labels

Model labels as special metro lines:

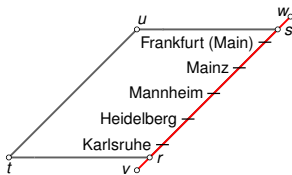
- put all labels between a pair of interchange stations into one parallelogram,
- allow parallelograms to change sides,



Modeling Labels

Model labels as special metro lines:

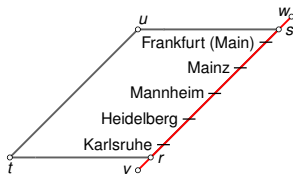
- put all labels between a pair of interchange stations into one parallelogram,
- allow parallelograms to change sides,



Modeling Labels

Model labels as special metro lines:

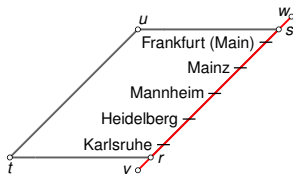
- put all labels between a pair of interchange stations into one parallelogram,
- allow parallelograms to change sides,
- **bad news**: a **lot** more planarity constraints



Modeling Labels

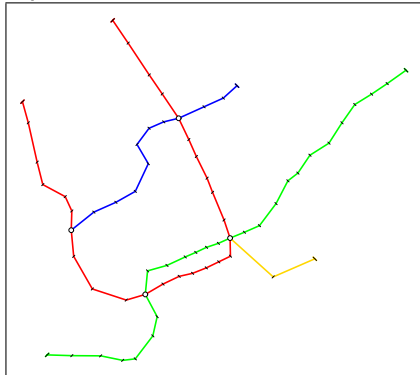
Model labels as special metro lines:

- put all labels between a pair of interchange stations into one parallelogram,
- allow parallelograms to change sides,
- **bad news**: a **lot** more planarity constraints
- **good news**: callback method helps



Labeling – Montréal

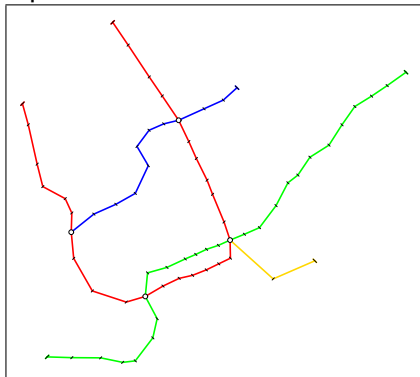
Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	65	66	3	4
reduced	20	21	3	
labeled	62	74	14	

Labeling – Montréal

Input



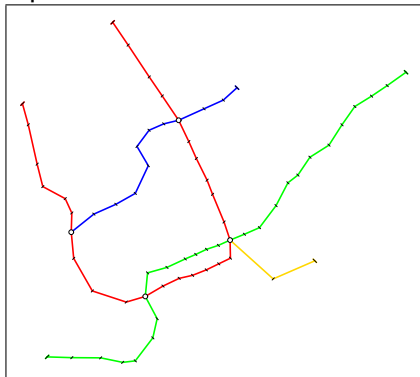
Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	65	66	3	4
reduced	20	21		
labeled	62	74	14	



MIP	constr.	var.
normal	86,493	21,209
faces	32,208	8,049
callback	4,400	8,049

Labeling – Montréal

Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	65	66	3	4
reduced	20	21		
labeled	62	74	14	

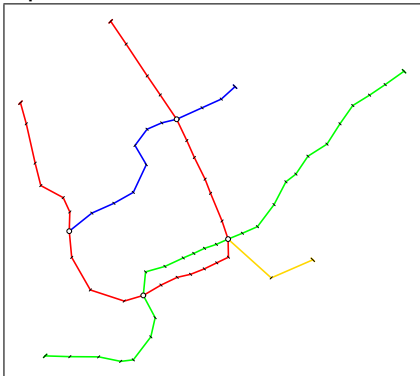


MIP	constr.	var.
normal	86,493	21,209
faces	32,208	8,049
callback*	4,400	8,049

*) 17 minutes w/o proof of opt.
 constr. of 60 edge pairs added

Labeling – Montréal

Input



Output (17 min.)



Labeling – Montréal



Labeling – Vienna

Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	90	96	8	5
reduced	44	50		
labeled	98	117	21	

Labeling – Vienna

Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	90	96	8	5
reduced	44	50		
labeled	98	117	21	

↓

MIP	constr.	var.
normal	219,064	53,538
faces	51,160	12,834
callback	9,144	12,834

Labeling – Vienna

Input



Input	$ V $	$ E $	fcs.	$ \mathcal{L} $
normal	90	96	8	5
reduced	44	50		
labeled	98	117	21	

↓

MIP	constr.	var.
normal	219,064	53,538
faces	51,160	12,834
callback*	9,144	12,834

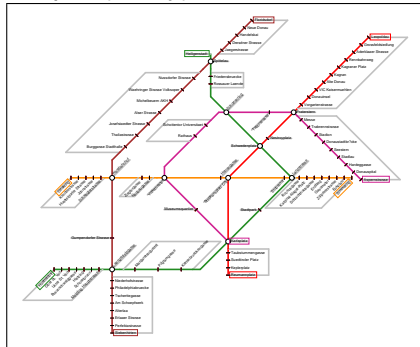
*) 1 day w/o proof of opt.
 constr. of 160 edge pairs added

Labeling – Vienna

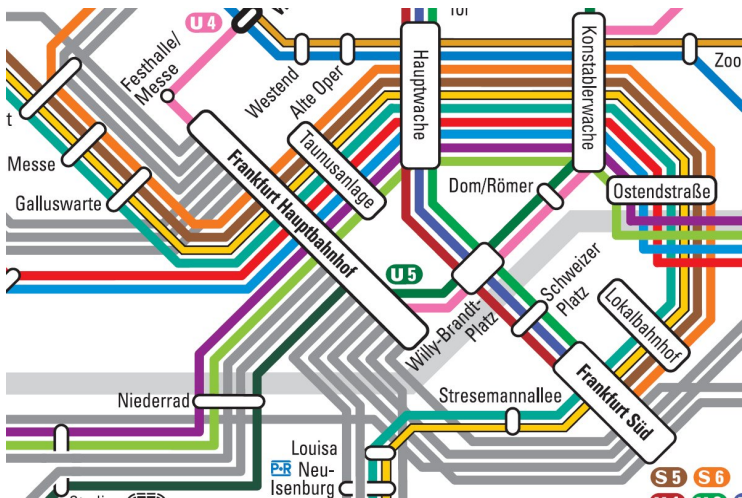
Input



Output (1 day)



To Do: Rectangular Stations & Multi-Edges



Summary (Metro Maps)

- METROMAPLAYOUT is NP-hard.
- Formulated and implemented MIP.
- Results comparable to manually designed maps.
- Reduced MIP size & runtime drastically.
- Combined layout and labeling.
- Our MIP can draw *any* kind of sketch “nicely”.

Summary (Metro Maps)

- METROMAPLAYOUT is NP-hard.
- Formulated and implemented MIP.
- Results comparable to manually designed maps.
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- Combined layout and labeling.
- Our MIP can draw *any* kind of sketch “nicely”.

To Do

- rectangular stations
- multi-edges
- user interaction (e.g. fixing certain edge directions)

Thank you for the attention.

Any questions?